OTHER SOCIAL EFFECTS: A TIME-SERIES ANALYSIS COMPARING SOCIAL VULNERABILITY CHANGES BETWEEN LOWER & HIGHER INCOME COMMUNITIES FROM FLOOD CONTROL PROJECTS

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Abstract

In January 2021, the United States Army Corps of Engineers (USACE) released a memorandum requiring future projects to be justified beyond National Economic Development benefits. The incorporation of Other Social Effects (OSE) benefits could be advantageous for better protecting low socioeconomic status (SES) neighborhoods in future flood and coastal storm projects. Past studies have analyzed different social vulnerability indices (SVI), but not in a historical context that analyzes the change in impacts during flood events. Three different methods of evaluating exposure indices (EI) were used within census tracts of Harris County, Texas using the 2019 American Community Survey and the CDC's SVI. These EIs were assessed with historical flood data to calculate OSE benefits. A time series model indicated that high SES neighborhoods have had more protection projects implemented than low SES neighborhoods and that the EI used in previous studies by USACE is an acceptable method of evaluating OSE benefits.

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1 Introduction

1.1 Current U.S. Army Corps of Engineers Economic Analysis

The role of the benefit-cost analysis (BCA) in U.S. Army Corps of Engineers' (USACE) projects is rooted in the Principles and Guidelines (P&G) of 1983[1]. The benefits that are calculated for a project are categorized into four main accounts: National Economic Development (NED), Regional Economic Development (RED), Other Social Effects (OSE) and Environmental Quality (EQ)[2]. However, as stated in the P&G, the objective is to, "Contribute to national economic development consistent with protecting the Nation's environment"[3]. Over time, USACE has created economic models that will calculate NED benefits for projects. These models go through extensive review, verifying that use of the model assures that the BCA is accurate, assuming the input values were properly gathered[4]. For example, flood-risk management (FRM) projects use the Hydrologic Engineering Center's Flood Damage Reduction Analysis (HEC-FDA) model to calculate the NED benefits of implementing a dike or levy to flood-prone regions[5]. The economist creates a structure inventory using water surface profiles created by hydraulic engineers to determine the structures that are threatened by flooding with

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1. Jonathan Armah et al., "Principles and Guidelines for Evaluating Federal Water Projects: US Army Corps of Engineers Planning and the Use of Benefit Cost Analysis," 2009.

2. "Economic and Environmental Principles and Guidelines for Water and Related Land Resources Implementation Studies." Washington D.C.: U.S. Army Corps of Engineers, March 10, 1983.

3. Armah et al. "Principles and Guidelines."

4. "Assuring Quality of Planning Models." Washington D.C.: U.S. Army Corps of Engineers, March 31, 2011.

5. "HEC-FDA Flood Damage Reduction Analysis." Davis, CA: U.S. Army Corps of Engineers Hydrologic Engineering Center, April 2016.

and without the implementation of a project in the study area. HEC-FDA will then apply a stage-damage function to determine the damage associated with those structures. The difference between the without-project and with-project damages is the NED benefits[6].

1.2 Assistant Secretary of the Army for Civil Works Memorandum

On January 5, 2021, the Assistant Secretary of the Army for Civil Works (ASA(CW)) released a memorandum requiring, "Equal consideration of the economic, environmental and social categories"[7]. While civil works projects, especially larger projects, have been analyzing all four benefit accounts, the ASA(CW) memo requires projects to use the other benefit accounts in the consideration and selection of an alternative. These additional benefits can have an impact on which alternatives are selected, especially in flood and storm projects. Since lower income communities are often hit hardest during storm events and NED benefits tend to disadvantage lower income communities, the inclusion of OSE benefits in the analysis of alternatives can alter how USACE conducts projects and improve areas that often have the most significant impacts to the people.

1.3 Socioeconomic Impact from Hurricane Harvey

Hurricane Harvey, hit the greater Houston area in 2017 and caused $125 billion in damage[8]. Studies show that 80% of residential parcels in majority black neighborhoods and 71% in majority Hispanic neighborhoods were flooded at least 5%, compared to 57% of residential

6. Ibid.

7. "Policy Directive - Comprehensive Documentation of Benefits in Decision Document." Washington D.C.: U.S. Army Corps of Engineers, January 5, 2021.

8. "Costliest U.S. Tropical Cyclones Tables Updated," National Oceanic and Atmospheric Administration, January 26, 2018, https://www.nhc.noaa.gov/news/UpdatedCostliest.pdf.

parcels flooded in majority white neighborhoods[9]. The issue with post-storm impacts is that the current USACE analysis using NED impacts does not properly account for impacts to lower income and predominately minority neighborhoods[10]. The HEC-FDA model used for FRM projects estimates the physical damages to flooded properties to calculate NED benefits. However, not only does lower income housing have less value, already making the communities disadvantaged in the NED analysis, but lower income communities have less capability to relocate during storms and are less likely to have proper flood insurance, making it more difficult to rebuild and recover from floods and storms[11]. The implementation of OSE benefits could help USACE evaluate the impact from flood and coastal storms to those in lower income communities. This study will evaluate how prior flood control projects have benefited higher income communities compared to lower income communities in Harris County, Texas to determine if the inclusion of OSE benefits in future studies could have a significant impact.

2 Literature Review

2.1 Explanation of OSE Benefits

OSE, as described in the 1983 Principles and Guidelines, "Registers plan effects from perspectives that are relevant to the planning process but are not reflected in the other three

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9. Kevin T Smiley, "Social Inequalities in Flooding inside and Outside of Floodplains during Hurricane Harvey," Environmental Research Letters (IOP Publishing, September 15, 2020), https://iopscience.iop.org/article/10.1088/1748-9326/aba0fe.

10. Susan E Durden and Maria Wegner-Johnson, "Other Social Effects: A Primer," April 2013.

11. Reilly Morse, "Environmental Justice Through the Eye of Hurricane Katrina," 2008, https://inequality.stanford.edu/sites/default/files/media/_media/pdf/key_issues/Environment_policy.pdf.

accounts",[12] leaving the account rather vague, compared to the other three accounts. USACE has translated the guidance on OSE to primarily focus on benefits related to safety, social vulnerability and emergency preparedness[13]. The greatest difficulty with utilizing OSE benefits is the method of quantifying the benefits monetarily.

2.2 Previous USACE Evaluations of OSE Benefits

During a USACE study on Hurricane Sandy, economists set up a method of quantifying OSE benefits in a manner that would produce an output similar to a BCA. OSE benefits were quantified by creating an exposure index (EI), which was a weighted sum of a population density and infrastructure index (PDII), a social vulnerability characterization index (SVCI) and an environmental and cultural resources index (ECRI). The PDII made up 80% of the EI, while the SVCI and ECRI each made up 10% of the EI. The PDII consisted of both the population density and the infrastructure, because "Census Bureau population statistics alone would not give an appropriate representation of things to be damaged in the study area"[14]. The SVCI considered vulnerable populations, such as people under 5 and over 65, people below the poverty threshold, and people who spoke a language other than English. The ECRI considers habitat, environmental and cultural resources that would be threatened. The weighted sum of these indices that make up the EI were multiplied by the change in the with and without project implementation probability that flood damages would occur to determine the change in the risk (ΔR). ΔR can be divided by

12. "Principles and Guidelines."

13. Durden and Wegner-Johnson, "Other Social Effects: A Primer."

14. "North Atlantic Coast Comprehensive Study Appendix B: Economics and Social Analyses," January 2015.

the cost of implementing an alternative to provide a ratio like a BCA, which provides a useful comparison of OSE risk between alternatives[15].

2.3 Other Social Vulnerability Indices

Social Vulnerability Indices (SVI) often utilize similar factors for the creation of the index. Common factors include age, gender, race, and socioeconomic status. Data for these factors are collected by the U.S. Census Bureau through the decennial census and the American Community Survey (ACS). A study conducted by Cutter et al. collected 250 different variables for social vulnerability. Through multicollinearity tests and normalization of the data, the 250 variables were narrowed to the 42 variables indicated in Table 1. Cutter et al. indicated that there is variability in SVIs across regions and there have been limited attempts to develop a larger process of using comparative indicators, largely due to the complicated nature of the variance[16].

15. Ibid.

16. Susan L. Cutter, Bryan J. Boruff, and W. Lynn Shirley, "Social Vulnerability to Environmental Hazards*," *Social Science Quarterly* 84, no. 2 (2003): pp. 242-261, https://doi.org/10.1111/1540-6237.8402002.

Table 1: Variables Names and Descriptions Used in Cutter et al. "Social Vulnerability to Environmental Hazards"*

Name	Description
MED_AGE90	Median age, 1990
PERCAP89	Per capita income (in dollars), 1989
MVALOO90	Median dollar value of owner-occupied housing, 1990
MEDRENT90	Median rent (in dollars) for renter-occupied housing units, 1990
PHYSICN90	Number of physicians per 100,000 population, 1990
PCTVOTE92	Vote cast for president, 1992—percent voting for leading party (Democratic)
BRATE90	Birth rate (number of births per 1,000 population), 1990
MIGRA_97	Net international migration, 1990–1997
PCTFARMS92	Land in farms as a percent of total land, 1992
PCTBLACK90	Percent African American, 1990
PCTINDIAN90	Percent Native American, 1990
PCTASIAN 90	Percent Asian, 1990
PCTHISPANIC90	Percent Hispanic, 1990
PCTKIDS90	Percent of population under five years old, 1990
PCTOLD90	Percent of population over 65 years, 1990
PCTVLUN91	Percent of civilian labor force unemployed, 1991
AVGPERHH	Average number of people per household, 1990
PCTHH7589	Percent of households earning more than $75,000, 1989
PCTPOV90	Percent living in poverty, 1990
PCTRENTER90	Percent renter-occupied housing units, 1990
PCTRFRM90	Percent rural farm population, 1990
DEBREV92	General local government debt to revenue ratio, 1992
PCTMOBL90	Percent of housing units that are mobile homes, 1990
PCTNOHS90	Percent of population 25 years or older with no high school diploma, 1990
HODENUT90	Number of housing units per square mile, 1990
HUPTDEN90	Number of housing permits per new residential construction per square mile, 1990
MAESDEN92	Number of manufacturing establishments per square mile, 1992
EARNDEN90	Earnings (in $1,000) in all industries per square mile, 1990
COMDEVDN92	Number of commercial establishments per square mile, 1990
RPROPDEN92	Value of all property and farm products sold per square mile, 1990
CVBRPC91	Percent of the population participating in the labor force, 1990
FEMLBR90	Percent females participating in civilian labor force, 1990
AGRIPC90	Percent employed in primary extractive industries (farming, fishing, mining, and forestry), 1990
TRANPC90	Percent employed in transportation, communications, and other public utilities, 1990
SERVPC90	Percent employed in service occupations, 1990
NRRESPC91	Per capita residents in nursing homes, 1991
HOSPTPC91	Per capita number of community hospitals, 1991
PCCHGPOP90	Percent population change, 1980/1990
PCTURB90	Percent urban population, 1990
PCTFEM90	Percent females, 1990
PCTF_HH90	Percent female-headed households, no spouse present, 1990
SSBENPC90	Per capita Social Security recipients, 1990

One primary SVI is the Center for Disease Control's (CDC) SVI (CDC-SVI). The CDC-SVI was created by the Agency for Toxic Substances and Disease Registry's (ATSDR) Geospatial Research, Analysis & Services Program (GRASP) to help identify areas that will most likely need support from hazardous events. The CDC-SVI uses, "15 social factors, including unemployment, minority status, and disability, and further groups them into four related themes"[17]. Additional information on the calculation of the CDC-SVI can be found in Appendix A.

2.4 Formulating SVI using Cluster Analysis

Evaluating the effectiveness of the EI used in previous USACE studies (USACE-EI) can be difficult for two reasons. First, the USACE-EI combines a SVI with the population density. Therefore, there are other considerations that vary from primary SVIs. Additionally, the USACE-EI does not group or score the values, so the data are not discrete and are difficult to compare across a geospatial region.

One method to transform continuous SVIs is using a k-means cluster analysis, as is evident in evaluating the impact of the Ebola virus in rural Liberia to derive some broad characterization of social vulnerability to facilitate discussion and mapping. A k-mean cluster analysis is an unsupervised, non-deterministic, numerical and iterative method of machine learning in which k number of clusters are assigned and each datum is assigned to a cluster that is most similar based on the mean value of the object[18]. In the study, a k-means clustering

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17. "CDC SVI Documentation 2018," Centers for Disease Control and Prevention (Centers for Disease Control and Prevention, June 22, 2021), https://www.atsdr.cdc.gov/placeandhealth/svi/documentation/SVI_documentation_2018.html.

18. Jyoti Yadav and Monika Sharma, "A Review of K-Mean Algorithm," *International Journal of Engineering Trends and Technology (IJETT)* 4, no. 7 (July 2013).

algorithm was used in R. “The NbClust package tested 25 metrics for k-means clustering with the number of clusters constrained to be between 2 and 7 and recommended 5 clusters based on majority rule among the available indices.” The use of the k-means cluster analysis to characterize the SVI helped determine the districts in Liberia that have high social vulnerability to the Ebola virus[19].

2.5 Analyzing of Flood Data

Measuring flood data on the national level goes back as far as 1889, with the United States Geological Survey (USGS). Today, analyzing flood data is often used in Geographic Information System (GIS) and involves complex analyses. There are two primary forms of hydrologic information: stage, which is the water depth above a reference; and flow or discharge, which is the volume of water flowing at a specified point. Modern flood assessments use hydraulic models, which determines the extent of flooding that can occur based on the topographic and geologic assessments of an area, combined with stage and flow data[20]. For use in this study, hydraulic models are too time consuming and require extensive knowledge of the models.

The Federal Emergency Management Agency (FEMA) produces flood maps that are used by insurance agencies to indicate regions that are sensitive to flooding. Wing et al. evaluated FEMA flood maps to determine their effectiveness. One complication of FEMA flood

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19. John A Stanturf et al., “Social Vulnerability and Ebola Virus Disease in Rural LIberia,” PLoS One, September 1, 2015.

20. Cara R Mays, “Using GIS and Historical Flood Data to Analyze the Risk and Vulnerability of a Rural Community, Past and Present,” KU ScholarWorks, May 7, 2018, https://kuscholarworks.ku.edu/bitstream/handle/1808/27919/Mays_ku_0099M_15915_DATA_1.pdf?sequence=1&isAllowed=y.

maps is that they are not consistent across the country, and the flood maps do not assess the flooding that can occur in smaller streams, which can often impact residential areas. The study conducted by Wing et al. determined that FEMA flood maps significantly underestimate population exposure and overestimate flood risk[21]. Due to the complicated nature of hydraulic models and the inaccuracy of FEMA flood maps, it is beneficial for this study to utilize historical stage data from major storm events in a small study area. Additionally, hydraulic models and FEMA flood maps represent the risk of future flooding and do not represent the flooding impacts from one region relative to another region. Historical stage data can be standardized so that the historical risk of flooding in one region can be compared to the other regions.

3 Data and Methods

The overall objective of the research was to determine if OSE benefits could have an impact on the location of USACE's flood and storm risk management projects using historical flood and storm events across Harris County, Texas, and if the current method of analysis used by USACE was effective.

Three separate OSE evaluations were created to determine how the method of analysis can impact the outcome and if there is a particular method that best suites the need of the evaluation. The first evaluation was the USACE-EI. The USACE-EI combined a census tract's population density with a social vulnerability index (SVI) determined by USACE (USACE-SVI).

21. Oliver Wing et al., "Estimates of Present and Future Flood Risk in the Conterminous United States," Environmental Research Letters 13, no. 3 (2018): p. 034023, https://doi.org/10.1088/1748-9326/aaac65.

The USACE-SVI was the sum of the percentages of different demographics within a census tract. The equation used for the USACE-SVI is shown below:

$$USACE\text{-}SVI = \%Age_{65+} + Age_{5-} + \%Income_{\ Sub\text{-}Poverty} + \%Nonproficient\ English$$ [22]

The second OSE evaluation was a k-means cluster analysis that used the USACE-SVI. The optimal number of clusters used in the cluster analysis was determined using a gap statistic graph. The final evaluation was the CDC-SVI. The three OSE evaluations were the dependent variables and time was the independent variable. The method of evaluating the impact of OSE benefits used a time-series analysis.

The values used to calculate the exposure index came from the American Community Survey (ACS) dataset from the U.S. Census Bureau, broken down by census tracts within Harris County, Texas[23]. The data for each census tract were geospatially joined to the census tract boundaries using the U.S. Census Bureau's Topologically Integrated Geographic Encoding and Referencing database (TIGER) data[24]. The historical flood data came from the Harris County Flood Warning System (FWS), operated by the Harris County Flood Control District (HCFCD). The flood data showed the recorded water height, in inches, above 187 flood gages throughout

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22. "North Atlantic Coast Comprehensive Study Appendix B: Economics and Social Analyses," January 2015.

23. Explore census data, accessed July 11, 2021, https://data.census.gov/cedsci/table?q=ACSDP1Y2019.DP05&tid=ACSDP1Y2019.DP05&hidePreview=true.

24. US Census Bureau, "Tiger/Line Shapefiles," The United States Census Bureau, December 14, 2020, https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-line-file.html.

Harris County bayous and tributaries[25]. Finally, CDC-SVI was pulled from the CDC's Agency for Toxic Substances and Disease Registry (ATSDR)[26].

The optimal number of clusters used in the k-mean cluster analysis was determined using the elbow method in R. GIS has a "Multivariate Clustering" tool to run a cluster analysis on geospatial data[27]. The cluster analysis was compared to both the USACE-EI analysis and the CDC-SVI to determine which method was more appropriate. The high and low socioeconomic status (SES) census tracts were compared to the historic flood data to indicate areas that have a higher likelihood of flooding impacts, as well as areas that are less likely to be impacted due to protection by levees. This analysis was used to calculate the change in risk (ΔR).

4 Results

4.1 Formatting and Preparing the Time Series Model

The OSE evaluations were formatted based on the information detailed in Section 3: Data and Methods. The optimal number of clusters used in the cluster analysis was determined using a gap statistic graph in R (Figure 1). The k-means cluster analysis did not create the clusters in order of low vulnerability to high vulnerability census tracts, so the groups had to be reordered (Table 2).

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25. About FWS (Harris County Flood Control District), accessed July 11, 2021, https://www.harriscountyfws.org/About.

26. "CDC SVI Documentation 2018," Centers for Disease Control and Prevention (Centers for Disease Control and Prevention, June 22, 2021), https://www.atsdr.cdc.gov/placeandhealth/svi/documentation/SVI_documentation_2018.html.

27. "How Multivariate Clustering Works," How Multivariate Clustering works-ArcGIS Pro | Documentation, accessed August 9, 2021, https://pro.arcgis.com/en/pro-app/latest/tool-reference/spatial-statistics/how-multivariate-clustering-works.htm.

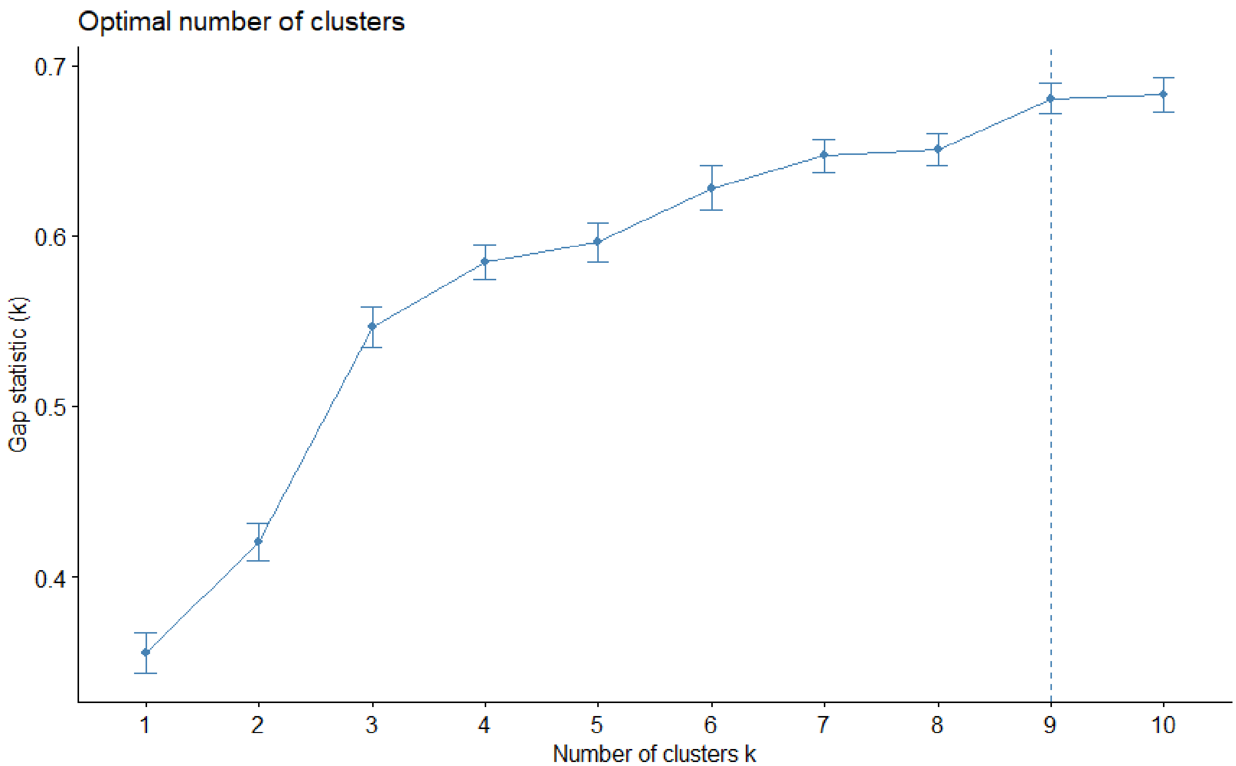

Figure 1: Gap Statistic Graph Indicating the Number of Clusters Used in the K-Means Cluster Analysis of USACE-SVI Scores in Harris County, TX

Table 2: Re-Ordered Clusters Based on Average USACE-SVI Value

Cluster Number	Average USACE-SVI	Ranked Cluster
1	50.7	1
2	55.6	2
3	112.9	8
4	123.3	9
5	63.5	3
6	76.7	6
7	87.3	7
8	72.4	5
9	65.9	4

The three evaluation methods were performed for each census tract across the county. In total, there were 786 census tracts used in the analysis. Table 3 shows the minimum, mean and maximum values for each evaluation method across the 786 census tracts. There were three census tracts that did not have a value in the CDC-SVI. Since the SVI ranges from zero to 11, the three tracts without a value used "NA". The three evaluation methods were standardized so that they can be compared against each other.

Table 3: Minimum, Mean, and Maximum Values from the Three Evaluation Methods

	USACE-EI	Cluster Analysis	CDC-SVI
Min	1.71	1	0
Mean	2161.65	5.04	1.83
Max	23738.46	9	11

The scores for each census tract were multiplied by the risk of flooding from the flood gauge data. There were ten major flood events recorded across 124 gauges in Harris County from 2008 to 2020 (Figure 2)[28]. The flooding for each flood event for each gauge was divided by the total flooding across the county for each event to determine the relative risk associated with that flood gauge. The relative risk shows if a gauge was better protected over time. A spatial join was performed in GIS to determine the flood gauge closest to the census tract. The flood risk for each census tract for each event was multiplied by the standardized values for the three evaluation methods to calculate the OSE benefits associated with the census tract.

28. "About," Harris County Flood Control District, accessed July 17, 2021, https://www.hcfcd.org/About/Harris-Countys-Flooding-History.

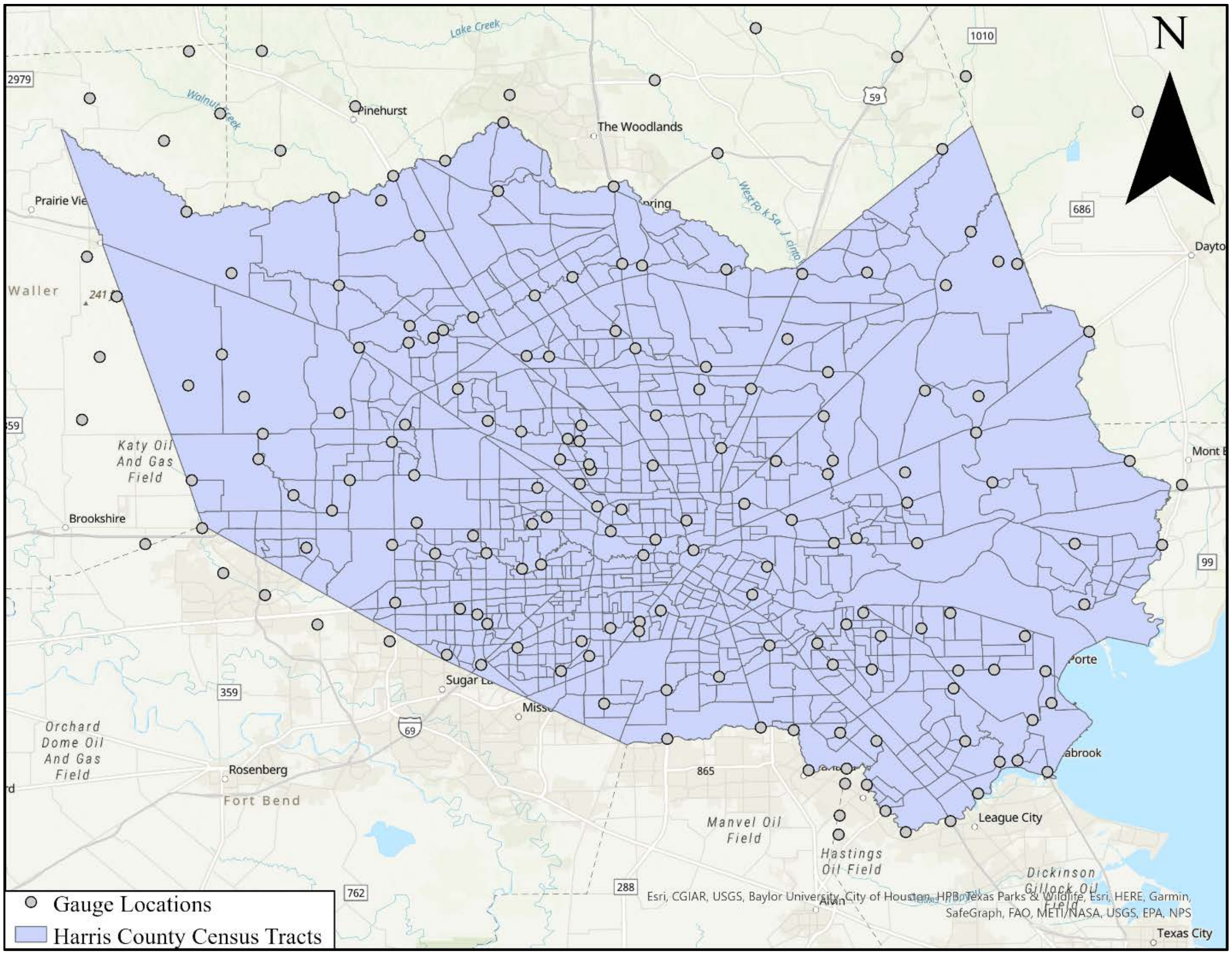

Figure 2: Harris County Census Tracts and Gauge Locations

4.2 Analysis of the Time Series Model

The first purpose of the study was to determine if there was a significant difference in the level of protection from flood control projects between high SES and low SES neighborhoods. An augmented Dickey-Fuller test was performed to determine if the time series data for the different OSE evaluations showed stationarity or not. The null hypothesis states that the data were non-stationary. As shown in Table 4, the p-values for total county cluster analysis evaluation were greater than .05, so there was not enough evidence to reject the null hypothesis, indicating that the data were non-stationary. Meanwhile, the p-values for the other two total county OSE evaluations were less than .05, indicating that the data were stationary. However, the p-value for every OSE evaluation for the high SES neighborhoods were greater than .05, indicating that the data were non-stationary. The finding of non-stationarity for the high SES neighborhoods indicates that there was a change in the data over time.

The change in the data over time for high SES neighborhoods can be attributed to the construction of flood prevention projects in those neighborhoods. One of the watersheds located in high SES neighborhoods is Cypress Creek. According to Harris County Flood Control District, the Cypress Creek watershed received $291 million in funding as part of the 2018 Bond Program to complete flood risk reduction projects[29]. The 2018 Bond Program was updated in May 2020, which is shown Appendix B. Of the 181 projects initiated as part of the program, eight have been completed, including four in the Cypress Creek watershed, and 136 are active. The evaluation of OSE benefits over time indicates less fluctuation in OSE benefits over time, as well as a slight increase in 2020, which can be attributed to the implementation of projects since 2018.

Table 4: P-Value of Augmented Dickey-Fuller Test

Total County USACE EI OSE	0.03
Total County Cluster Analysis OSE	0.99
Total County CDC SVI OSE	0.03
High SES USACE EI OSE	0.64
Low SES USACE EI OSE	0.01
High SES Cluster Analysis OSE	0.78
Low SES Cluster Analysis OSE	0.39
High SES CDC SVI OSE	0.85
Low SES CDC SVI OSE	0.06

29. "Active Construction Projects," Harris County Flood Control District, accessed July 18, 2021, https://www.hcfcd.org/Resources/Interactive-Mapping-Tools/Active-Construction-Projects.

4.3 Comparison and Analysis of OSE Evaluations

The second purpose of the study was to determine if there was a particular OSE evaluation that would be preferable over the other evaluations. A test of significant difference in means between the standardized values of the three evaluations was used to compare the three evaluations. The null and alternative hypotheses are shown below:

H_0: true different in means are equal to 0

H_a: true difference in means is not equal to 0

As shown in Table 5, the p-values for the relationship between the three were greater than .05, so there was not enough evidence to reject the null hypothesis, indicating that the different analyses were similar. Furthermore, the p-value of the Dickey-Fuller test for the total county cluster analysis indicated some level of difference, albeit non-significant, from the other two evaluations. Additionally, the cluster analysis did not provide a definitive difference between the low SES and high SES neighborhoods, which would indicate that the cluster analysis was likely not the best evaluation method used for future projects.

Table 5: P-Values of Comparison Between OSE Analyses

USACE EI to Cluster Analysis	USACE IE to CDC SVI	CDC SVI to Cluster Analysis
0.18	0.28	0.46

A visual comparison was also used to show the similarities and differences between the remaining two OSE evaluations (Figure 3 and Figure 4). As shown in the two figures, there are some similarities on the southwestern edge of the county, but the CDC SVI evaluation has less variance within that region of the county. Additionally, the CDC SVI evaluation appears to show a greater impact in the north-central, south-central, and east-central regions of the county, while the USACE EI evaluation shows a greater impact in the west-central region of the county, likely due to the higher population density within that region of the county. Ultimately, the USACE EI evaluation has a higher weight on population density than the CDC SVI evaluation, but the two evaluations produce similar results, so both appear to be suitable methods of evaluation for calculating OSE benefits.

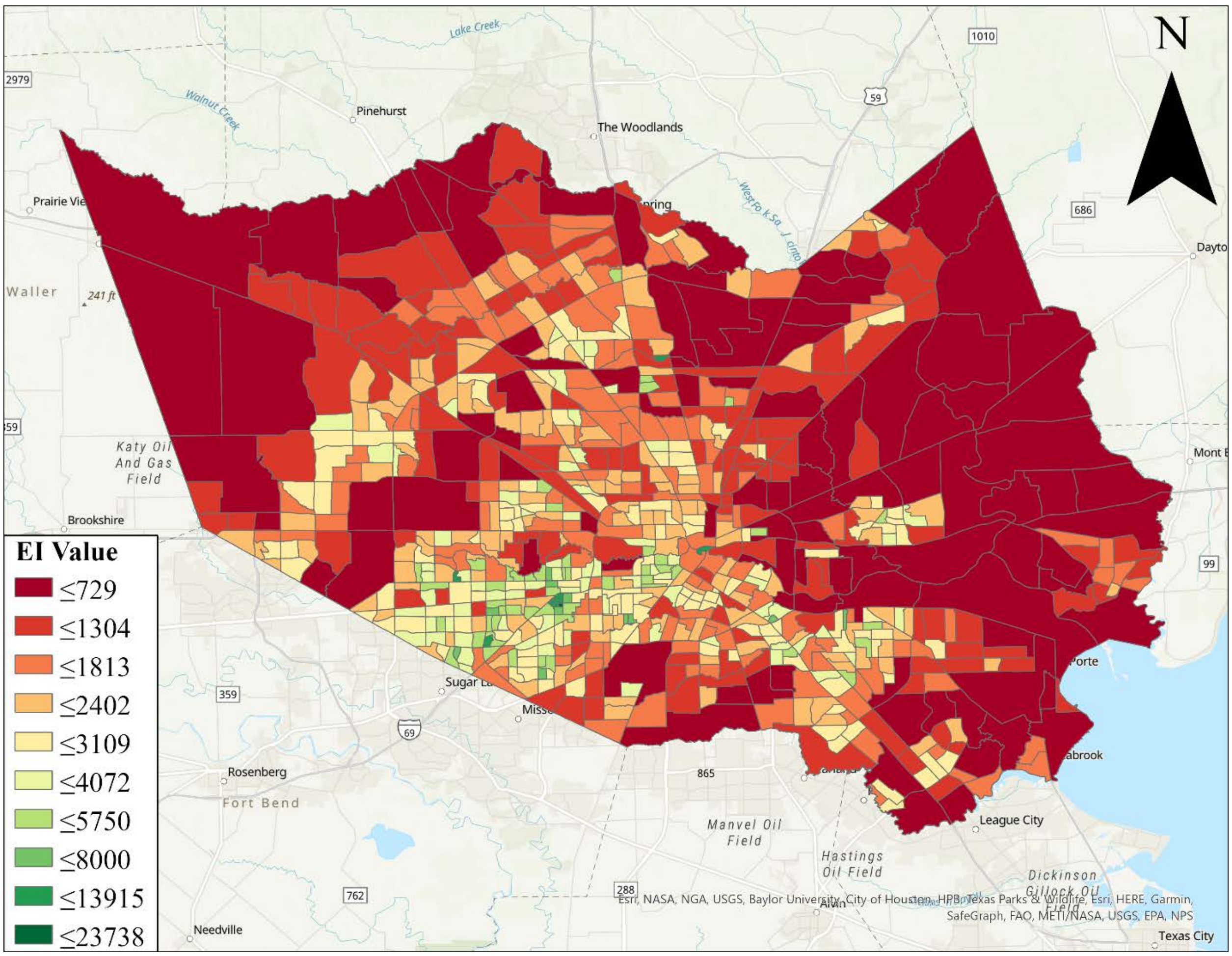

Figure 3: USACE EI Values by Census Tract Across Harris County, TX

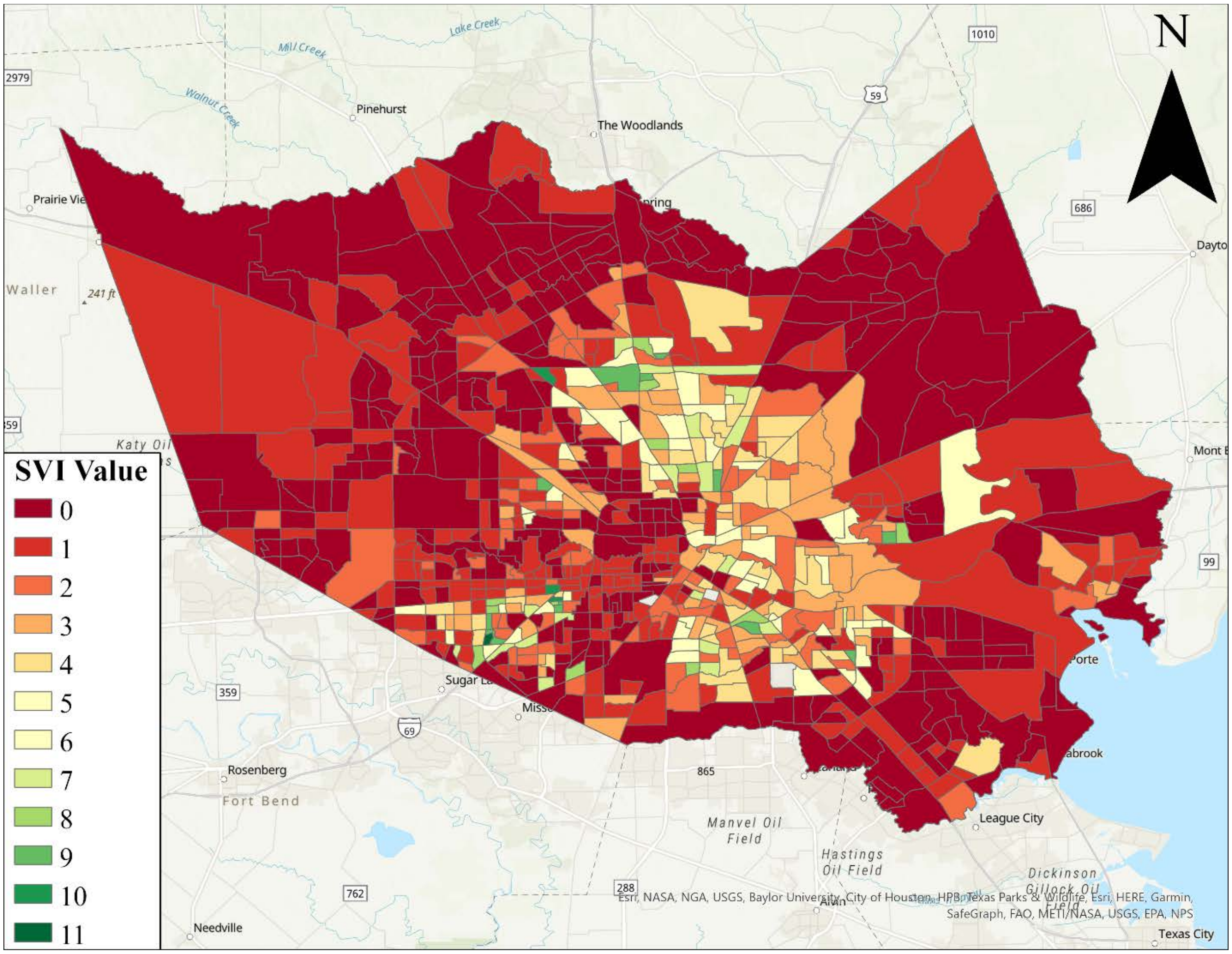

Figure 4: CDC SVI Values by Census Tract Across Harris County, TX

5 Conclusion

The intention of this analysis was to research and evaluate different methods of calculating OSE benefits using various SVIs and historical flood data and to analyze how OSE evaluations could impact the outcome of flood and coastal storm projects. The three different OSE evaluations used were an EI created by USACE for previous projects, a k-means cluster analysis using a similar SVI to the USACE-EI, and the CDC-SVI. The OSE evaluations were calculated for each census tract within Harris County, Texas, and were multiplied by historical flood gauge data collected from 124 gauge locations across Harris County.

The results of the analysis indicate that there was a significant change in OSE benefits for high SES neighborhoods overtime, but not for low SES neighborhoods. The significant change in OSE benefits were indicated using the USACE-EI evaluation and the CDC-SVI evaluation, but not for the Cluster Analysis evaluation. The change in OSE benefits appeared to be associated with the implementation of flood control projects in high SES neighborhoods, indicating that OSE benefits increase with the implementation of flood projects. The Cluster Analysis evaluation did not follow similar trends to the USACE-EI and CDC-SVI evaluations, so the Cluster Analysis does not appear to be the ideal form of OSE evaluation for future analyses. However, both the USACE-EI evaluation and CDC-SVI evaluation appear to be comparable, and the USACE-EI may be a more appropriate form of evaluation.

The results of this analysis indicate that OSE benefits should be used more significantly in future USACE flood and coastal storm projects to analyze the impacts that projects can have on lower SES neighborhoods and to select an appropriate project that will protect the threatened population.

There were limitations to this analysis that could continue to be evaluated in the future. First, the evaluations of OSE benefits used historical flood data, which represents the water level at a water source above a marked datum. Historical flood data were used because modern flood analysis often require complex hydraulic models and future projections based on the changing conditions and typography of the area. However, USACE projects use these complex hydraulic models and projected flood conditions in the formulation of OSE benefits. With additional time and resources, it would be beneficial to re-evaluate the results of this analysis using different flood data to determine if proper hydraulic modeling can change the outcome of the analysis. Additionally, the current analysis evaluates OSE benefits on a relatively small study area. Harris

County, Texas was used as the study area for this research because the county is one of the more storm and flood prone regions in the country. However, factors that contribute to an SVI can vary by region. A future study could use this research design in other areas of the nation to determine how different regions and different SVI factors could impact the outcome of OSE benefits. This would help USACE determine the best factors to use in their EI to create a more homogeneous index for other regions of the nation. This study, as well as future studies, can help USACE set up the necessary policies to streamline the format of OSE benefits so that future flood and coastal storm projects are created with the people's best interest in mind.

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Appendix A: CDC SVI 2018 Documentation - 1/31/2020

Introduction

What is Social Vulnerability?

Every community must prepare for and respond to hazardous events, whether a natural disaster like a tornado or a disease outbreak, or an anthropogenic event such as a harmful chemical spill. The degree to which a community exhibits certain social conditions, including high poverty, low percentage of vehicle access, or crowded households, may affect that community's ability to prevent human suffering and financial loss in the event of disaster. These factors describe a community's social vulnerability.

What is CDC Social Vulnerability Index?

ATSDR's Geospatial Research, Analysis & Services Program (GRASP) created Centers for Disease Control and Prevention Social Vulnerability Index (CDC SVI or simply SVI, hereafter) to help public health officials and emergency response planners identify and map the communities that will most likely need support before, during, and after a hazardous event.

SVI indicates the relative vulnerability of every U.S. Census tract. Census tracts are subdivisions of counties for which the Census collects statistical data. SVI ranks the tracts on 15 social factors, including unemployment, minority status, and disability, and further groups them into four related themes. Thus, each tract receives a ranking for each Census variable and for each of the four themes, as well as an overall ranking.

In addition to tract-level rankings, SVI 2010, 2014, 2016, and 2018 also have corresponding rankings at the county level. Notes below that describe "tract" methods also refer to county methods.

How can CDC SVI help communities be better prepared for hazardous events?

SVI provides specific socially and spatially relevant information to help public health officials and local planners better prepare communities to respond to emergency events such as severe weather, floods, disease outbreaks, or chemical exposure.

CDC SVI can be used to:

- Allocate emergency preparedness funding by community need.
- Estimate the type and amount of needed supplies such as food, water, medicine, and bedding.
- Decide how many emergency personnel are required to assist people.
- Identify areas in need of emergency shelters.
- Create a plan to evacuate people, accounting for those who have special needs, such as those without vehicles, the elderly, or people who do not speak English well.
- Identify communities that will need continued support to recover following an emergency or natural disaster.

Important Notes on CDC SVI Databases

✦ SVI 2014, 2016, and 2018 are available for download in shapefile format from https://www.atsdr.cdc.gov/placeandhealth/svi/data_documentation_download.html. SVI 2014 and

2016 are also available via ArcGIS Online. Search on "CDC's Social Vulnerability Index."

- For SVI 2000 and 2010, keep the data in geodatabase format when downloading from https://www.atsdr.cdc.gov/placeandhealth/svi/data_documentation_download.html. Converting to shapefile changes the field names.
- ACS field names have changed between SVI 2016 and 2018. Name changes are noted in the Data Dictionary below.
- For US-wide or multi-state mapping and analysis, use the US database, in which all tracts are ranked against one another. For individual state mapping and analysis, use the state-specific database, in which tracts are ranked only against other tracts in the specified state.
- Starting with SVI 2014, we've added a stand-alone, state-specific Commonwealth of Puerto Rico database. Puerto Rico is not included in the US-wide ranking.
- Starting with SVI 2014, we've added a database of Tribal Census Tracts (https://www.census.gov/newsroom/blogs/random-samplings/2012/07/decoding-state-county-censustracts-versus-tribal-census-tracts.html). Tribal tracts are defined independently of, and in addition to, standard county-based tracts. The tribal tract database contains only estimates, percentages, and their respective margins of error (MOEs), along with the adjunct variables described in the data dictionary below. Because of geographic separation and cultural diversity, tribal tracts are not ranked against each other nor against standard census tracts.
- Tracts with zero estimates for total population (N = 645 for the U.S.) were removed during the ranking process. These tracts were added back to the SVI databases after ranking. The TOTPOP field value is 0, but the percentile ranking fields (RPL_THEME1, RPL_THEME2, RPL_THEME3, RPL_THEME4, and RPL_THEMES) were set to -999.

- For tracts with > 0 TOTPOP, a value of -999 in any field either means the value was unavailable from the original census data or we could not calculate a derived value because of unavailable census data.
- Any cells with a -999 were not used for further calculations. For example, total flags do not include fields with a -999 value.
- Whenever available, we use Census-calculated MOEs. If Census MOEs are unavailable, for instance when aggregating variables within a table, we use approximation formulas provided by the Census in Appendix A (pages A-14 through A-17) of *A Compass for Understanding and Using American Community Survey Data* here: https://www.census.gov/content/dam/Census/library/publications/2008/acs/ACSGeneralHandbook.pdf If more precise MOEs are required, see Census methods and data regarding Variance Replicate Tables here: https://www.census.gov/programs-surveys/acs/technical-documentation/variance-tables.html. For selected ACS 5-year Detailed Tables, "Users can calculate margins of error for aggregated data by using the variance replicates. Unlike available approximation formulas, this method results in an exact margin of error by using the covariance term."
- The U.S. Census Bureau reports that data collection errors prohibited the inclusion of income and poverty data from Rio Arriba County, New Mexico. Please see a more detailed explanation provided by the Census Bureau here: https://www.census.gov/programs-surveys/acs/technicaldocumentation/errata/125.html.
- FIPS codes are generally defined as text to preserve leading zeros (0s). If you're working with csv files, leading 0s are required to properly join or merge tables. ArcGIS maintains

leading 0s in the FIPS code fields of csv files. To preserve leading 0s and create an Excel file in Excel for Office 365, follow these steps:

- Open a blank worksheet in Excel.
- Click Data in the menu bar and choose the icon From Text/CSV o Navigate to the csv file and choose to Import o In the dialog box that opens, choose to Transform Data
- In the Power Query Editor dialog box, for each of the FIPS columns (ST, STCNTY, FIPS for tracts and ST, FIPS for counties), right click the column name and choose to Change Type to Text.
- As prompted in the Change Column Type dialog box, choose to Replace current. Click Close and Load.
- Save As an Excel xlsx file.

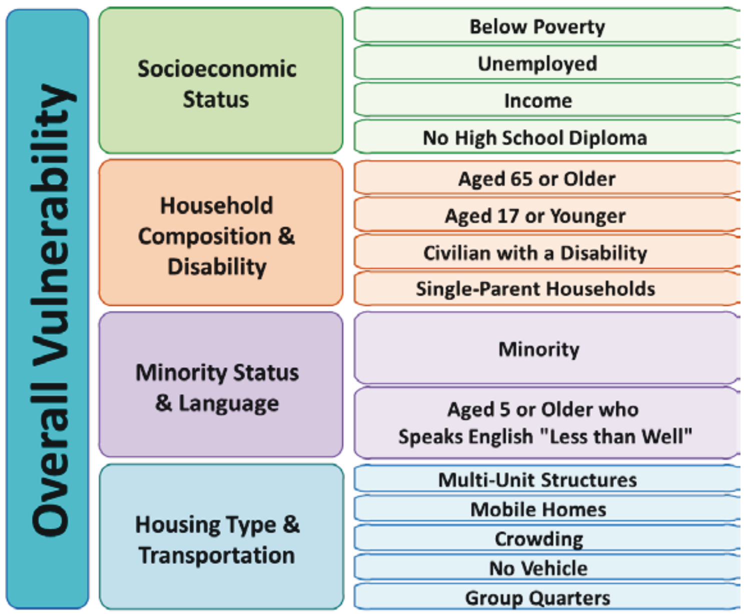
✦ See the ***Methods*** section below for further details.

✦ Questions? Please visit the SVI website at http://svi.cdc.gov for additional information or email the SVI Coordinator at svi_coordinator@cdc.gov.

Methods

Variables Used

American Community Survey (ACS), 2014-2018 (5-year) data for the following estimates:



Text version of overall vulnerability image:

- Socioeconomic Status
    - Below Poverty
    - Unemployed
    - Income
    - No High School Diploma
- Household Composition & Disability
    - Aged 65 or Older
    - Aged 17 or Younger
    - Civilian with a Disability
    - Single-Parent Households
- Minority Status & Language
    - Minority

    - Speaks English “Less than Well”
- Housing Type & Transportation
    - Multi-Unit Structures
    - Mobile Homes
    - Crowding
    - No Vehicle
    - Group Quarters

For SVI 2018, we included two adjunct variables, 1) 2014-2018 ACS estimates for persons without health insurance, and 2) an estimate of daytime population derived from LandScan 2018 estimates. These adjunct variables are excluded from SVI rankings.

Raw data estimates and percentages for each variable, for each tract, are included in the database. In addition, the margins of error (MOEs) for each estimate, at the Census Bureau standard of 90%, are also included. Confidence intervals can be calculated by subtracting the MOE from the estimate (lower limit) and adding the MOE to the estimate (upper limit). Because of relatively small sample sizes, some of the MOEs are high. It’s important to identify the amount of error acceptable in any analysis.

Rankings

We ranked Census tracts within each state and the District of Columbia, to enable mapping and analysis of relative vulnerability in individual states. We also ranked tracts for the entire United States against one another, for mapping and analysis of relative vulnerability in multiple states, or across the U.S. as a whole. Tract rankings are based on percentiles. Percentile ranking values range from 0 to 1, with higher values indicating greater vulnerability.

For each tract, we generated its percentile rank among all tracts for 1) the fifteen individual variables, 2) the four themes, and 3) its overall position.

Theme rankings: For each of the four themes, we summed the percentiles for the variables comprising each theme. We ordered the summed percentiles for each theme to determine theme-specific percentile rankings.

The four summary theme ranking variables, detailed in the Data Dictionary below, are:

- **Socioeconomic - RPL_THEME1**
- **Household Composition & Disability - RPL_THEME2**
- **Minority Status & Language - RPL_THEME3**
- **Housing Type & Transportation - RPL_THEME4**

Overall tract rankings: We summed the sums for each theme, ordered the tracts, and then calculated overall percentile rankings. Please note; taking the sum of the sums for each theme is the same as summing individual variable rankings. **The overall tract summary ranking variable is RPL_THEMES**.

Flags

Tracts in the top 10%, i.e., at the 90th percentile of values, are given a value of 1 to indicate high vulnerability. Tracts below the 90th percentile are given a value of 0.

For a theme, the flag value is the number of flags for variables comprising the theme. We calculated the overall flag value for each tract as the number of all variable flags.

For a detailed description of SVI variable selection rationale and methods, see A Social Vulnerability Index for Disaster Management (https://www.atsdr.cdc.gov/placeandhealth/svi/img/pdf/Flanagan_2011_SVIforDisasterManagement-508.pdf).

Reproducibility Caveat

When replicating SVI using Microsoft Excel or similar software, results may differ slightly from databases on the SVI website or ArcGIS Online. This is due to variation in the number of decimal places used by the different software programs. For purposes of automation, we developed SVI using SQL programming language. Because the SQL programming language uses a different level of precision compared to Excel and similar software, reproducing SVI in Excel may marginally differ from the SVI databases downloaded from the SVI website. For future iterations of SVI, beginning with SVI 2018, we plan to modify the SQL automation process for constructing SVI to align with that of Microsoft Excel. If there are any questions, please email the SVI Coordinator at svi_coordinator@cdc.gov.

Appendix B: UPDATE TO THE 2018 HARRIS COUNTY FLOOD CONTROL DISTRICT BOND PROGRAM

The Harris County Flood Control District (District) has submitted an update of the 2018 Harris County Flood Control District Bond Program (Program) for Commissioners Court for consideration on May 19, 2020. Commissioners Court approved the update.

This update includes typographical corrections, funding updates, and other clarifications to the 2018 District Bond Program. Future updates are planned to be presented to Commissioners Court biannually in March and September. The updated Program is included with this transmittal as Attachment 1.

Please note that throughout this memorandum and the attachments, Bond projects will reference a "Bond ID." The Bond ID is the unique identifier for each Bond project. A Bond project can have multiple projects associated with it. The tables in this memorandum and attachments list the Bond IDs for all Bond projects.

Below are a few of the highlighted changes contained in this update:

- Funding updates were made to the Brays Bayou, Hunting Bayou, White Oak Bayou, and Clear Creek Federal projects based on the 2018 Bipartisan Budget Act appropriations, associated Corps work plan, and the subsequent updated agreements with the Corps for these projects. Over $357M in federal funds were made available to help complete these projects.
- Some project costs were updated based on the development of engineer's estimates that have subsequently provided more accurate construction costs.
- Reduced the $500M contingency line item because these funds are not currently available.

- Any Bond projects without a Bond ID were assigned a unique ID to provide consistency in descriptions and naming conventions. These were adopted on a case by case basis through court authorizations to assign them as Bond projects became active.
- Added a new Bond project (Bond ID Z-11) to fund community engagement efforts.
- $678M in partnership funds have been secured via agreements (combined with $257M in local funds for $935M in projects), and these partnership funds are now acknowledged in the update.
- Prior to this update there were 241 total Bond projects, of which the District has initiated 208.
- With this update there are now 181 total Bond projects, with a consolidation of 64 of the initiated projects in which there were:
    - o Sixteen (16) Subdivision Drainage Improvement Bond projects consolidated into one (1) Countywide Subdivision Drainage Improvement Bond project
    - o Seventeen (17) Buyout Bond projects consolidated into one (1) Countywide Buyout Bond project o Twenty (20) Storm Repair Bond projects consolidated into one (1) Countywide

      Storm Repair Bond project o Eleven (11) other Bond projects combined into existing Bond projects for efficiency in project management and due to similar benefits of those Bond projects

With these changes in place, the updated project numbers are as follows:

	2018 Bond Project List (2018 original)	2018 Bond Project List (March 2020 update)
Total Bond Program Projects	241**	181
Initiated	208	144 (64 consolidated)*
Active (includes 4 added projects)	*200*	*136*
Completed	*8*	*8*
Not Initiated	37	37

* 64 of the active projects have been consolidated for efficiency and project management purposes. Bond funds associated with those individual Bond projects are now combined. See Exhibit 1 for a graphic showing the Bond project consolidations. ** The 241 Bond projects is derived from the 237 Bond projects on the original Bond Project List, plus the 4 new Bond projects added through Commissioners Court approval.

A comparison summary is included with this transmittal as Attachment 2. A detailed list of all changes is included as Attachment 3.

Completed Projects

Since the initiation of the Program on August 28, 2018, the District has completed eight Bond projects. These Bond projects are listed below and detailed in Attachment 4. Bond IDs CI-021, CI-016, CI-020, CI-035, and CI-036 are engineering investigations. Bond IDs F-59 and F-21 were projects completed without using Bond funds, but were in the original Bond list. The reason for this is that the projects were ready to start construction before the Bond funding was available.

The District did not want to delay construction of these projects and chose to fund them with available cash.

Bond ID CI-039 was simply a cost share, and the District has provided the requested funding to the City of Nassau Bay which has since completed the construction project. One-page summaries for each completed Bond project are attached with this transmittal and are posted on the District website.

Completed Bond Projects			
No.	**Watershed**	**Bond ID**	**Title**
1	Armand Bayou	CI-021	Brookglen Flooding Mitigation Analysis
2	Buffalo Bayou	CI-016	Investigations of Bridges and Potential Channel Bypasses over Buffalo Bayou
3	Buffalo Bayou	F-59	Spring Branch Creek Stabilization
4	Clear Creek	CI-039	Partnership Project with Nassau Bay to Reduce the Risk of Flooding
5	Cypress Creek	CI-020	Investigation of Potential Detention Sites Around Cypress Creek and Stuebner Airline
6	Cypress Creek	CI-035	Update to 2003 Texas Water Development Board Cypress Creek Tributary Study and Investigate Expanding Stormwater Detention Basins in Cypress Creek Watershed

7	Cypress Creek	CI-36	Investigation of Additional Detention Volume at K500-01-00 Stormwater Detention Basin
8	Cypress Creek	F-21	Restore Channel Conveyance Capacity on K129-00-00

Additionally, multiple infrastructure repair projects associated with Hurricane Harvey have been completed. These storm repair projects include several hundred individual construction sites that have been combined into 25 construction packages. For brevity, the completed individual District projects are not listed in this memorandum, but can be seen visually in the attached *Active and Completed Bond Projects* exhibit.

Bond Projects Added to the Bond Program

The District added four (4) new Bond projects and assigned twelve (12) new Bond IDs to existing Bond projects. These new Bond projects, newly assigned Bond IDs, along with details of the District Countywide projects, are listed below and in the attachments. New Bond projects are required when the District cannot track new work with an existing Bond project. Each of these new Bond projects were previously presented to and approved by Commissioners Court. The District plans to complete all Bond projects included in the Program in addition to the new Bond projects that have been added.

Of the four new Bond projects, two Bond Implementation Manager (BIM) Bond IDs, F-122 and F123, were added to the Program. The BIM Bond projects for Cedar Bayou and Halls Bayou are a new approach for the District in response to the directive to complete the Program as quickly as possible. All of the Bond projects in these two watersheds will be active at the same time with the goal of delivering all projects in less than ten years. The BIM Bond projects are funded through a pro-rata reallocation of funds from the other Bond projects in the watershed that the BIM will manage.

Due to the increased level of community engagement associated with the Program, a new Countywide Communications Bond project with the Bond ID, Z-11, was added. Additionally, a new project for a study in Carpenters Bayou was created and funded through a reallocation of funding from the Countywide Ongoing Planning Bond project, Z-03. A list of all new Bond projects is included as Attachment 4. New projects will be documented on www.hcfcd.org.

New Bond IDs Added to the Bond Program			
No.	**Watershed**	**Bond ID**	**Title**
1	Carpenters Bayou	F-124	Investigations of General Drainage Improvements along Carpenters Bayou
2	Cedar Bayou	F-123	Management, Right-Of-Way acquisition, Design, and Construction of Projects in the Cedar Bayou watershed
3	Halls Bayou	F-122	Management, Right-Of-Way Acquisition, Design, and Construction of Projects in the Halls Bayou watershed
4	Countywide	Z-11	Community Engagement and Public Outreach Services

Bond Projects with Multiple District Projects

Several Bond IDs are intended to generate multiple new District projects. In the table below, for example, you'll see that Bond ID Z-02, "Partnership Projects with Municipalities, Authorities, and Other Districts in Harris County," already involves ten distinct District partnership projects that are not associated with any other Bond project. The District requested and was granted authorization by Commissioners Court to negotiate with each partner for these individual District partnership projects across Harris County.

	Countywide Bond Projects With Multiple District Projects			
No.	**Bond ID**	**District ID**	**Watershed**	**Title**
1	Z-02 Partnership Projects with Municipalities, Authorities and Other Districts	A100-00-00-P006	Clear Creek	Lower Clear Creek Flood Mitigation Plan
2		D100-00-00-E016	Brays Bayou	Detention on City of Houston Right-Of-Way at S. Braeswood and the West Loop
3		D100-00-00-P011	Brays Bayou	City of Bellaire Master Drainage Plan
4		D112-00-00-E001	Brays Bayou	Drainage Improvements in Westbury
5		D500-11-00-E001	Brays Bayou	Meyergrove Detention Basin
6		O101-01-00-E001	Goose Creek	City of Baytown Drainage Improvements
7		P152-00-00-E002	Greens Bayou	Drainage Improvements within Water Control and Improvement District 109

8		U106-00-00-E004	Addicks Reservoir	Drainage Improvements within Spencer Road PUD
9		W100-00-00-P011	Buffalo Bayou	St. George Place/TIRZ 1 Drainage Improvements Study
10		Z100-00-00-P036	Countywide	Houston Ship Channel Watershed Sediment Study
11	Z-03 Countywide Planning	P100-00-00-P002	Greens Bayou	Watershed Planning Study for the Lower Greens Bayou Watershed
12		Z100-00-00-P033	Countywide	Updates to the Watershed Master Plan
13		Z100-00-00-P035	Countywide	Countywide Level of Service Analysis
14	Z-04 Partnerships with HCED	U502-02-00-E007	Addicks Reservoir	John Paul Landing Central Cell Excavation
15	Z-05 Emerging Technologies	W100-00-00-W002	Buffalo Bayou	Buffalo Bayou Park Revegetation and Biostabilization
16		W100-00-00-Y002	Buffalo Bayou	Fluvial Geomorphic Assessment to Improve Bank Stability and Resiliency of Buffalo Bayou
17		Z100-00-00-P029	Countywide	Drainage Reuse Initiative (DRI) Feasibility Study

Active Projects

The District is currently working on 136 Bond projects from the Program. Projects that are in construction or have completed construction are shown in the attached *Active and Completed Bond Projects* exhibit.

Some of these Bond Projects are actually programs that consist of several individual District projects, such as the Subdivision Drainage Improvement Project (Z-SUBDIV). This Bond project is actually 88 separate District projects that are managed by the Harris County Engineering Department's Recovery & Resiliency Division.

Similarly, some of the active construction projects are packages of several smaller construction sites. For example, the active construction District project, Z100-00-00-X283, is one large construction project consisting of ten different separate construction sites under Bond ID ZStormRep. There are currently 18 of these type of District construction projects underway, resulting in 206 separate, active construction sites.

Taking into account all of the projects, including the programs, there are 474 individual District projects in progress related to the Bond Program.

These District projects are in various stages of the flood damage reduction project lifecycle. The table below presents a breakdown of District projects and their current stage in the project lifecycle. Home buyout and communications District projects are in the "Other" category.

Project Lifecycle Stage	**Number of Projects**
Feasibility Study	47
Preliminary Engineering	50
Design	128

Construction	223
Operation & Maintenance	2
Other	24
Total	474

Curriculum Vita

Gerard (Jay) Walter has spent the past three years working as a regional economist for the United States Army Corps of Engineers in Buffalo, NY. While working in Buffalo, Jay has worked on a broad range of projects, including various economic, analytical, and geospatial work. He has a particular interest in machine learning and artificial intelligence.

Jay completed a Bachelor of Science in Mathematics with a Concentration in Actuarial Science and a Bachelor of Art in Economics from the University at Buffalo in 2019. In addition, Jay will complete his Master of Science in Data Analytics and Policy with a Concentration in Geospatial Analysis from Johns Hopkins University in Summer 2021.